The Impact of QMB Enrollment on Medicare Costs and Service Utilization

Final Report

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EXECUTIVE SUMMARY

The Medicare program's cost-sharing provisions -- its premiums, deductibles, and copayments -- can present a substantial financial hardship for low-income beneficiaries. To alleviate some of this burden, Congress enacted the Qualified Medicare Beneficiary (QMB) program. Under this program, implemented in 1990, state Medicaid programs are required to pay Medicare premiums, deductibles and copayments for low-income elderly beneficiaries and other disabled Medicare enrollees meeting certain income and asset criteria. By providing nearly first-dollar coverage to program enrollees, the QMB program substantially reduces their medical care costs.

This study's purpose is two-fold: to determine whether reductions in health care costs generated by QMB enrollment increase access to care and to compare health expenditures of the QMB enrolled population with those of elderly Medicare beneficiaries who are eligible for but not enrolled in the program. Using data from the Medicare Current Beneficiary Survey (MCBS) and the MCBS National Claims History File, we analyzed the demographic characteristics and health care expenditures of individuals participating in the QMB program with those of eligible non-enrollees.

To determine the impact of QMB enrollment on health care utilization, we created a two-part model of demand (Manning et al., 1987) representing the decision to use medical care as well as the intensity of service utilization. In addition, we developed a multi-

equation system to provide unbiased estimates of QMB enrollment and to account for the possibility that beneficiaries enrolled in the program to obtain treatments that would improve their health status. Throughout the text, this possibility is discussed as "adverse selection." We define adverse selection as a decision made by a QMB-eligible beneficiary *or the beneficiary's agent* (e.g., a family member, hospital social worker, legal aid staff, or outreach volunteers) to enroll the beneficiary in QMB based on the expectation that he or she will incur large health care expenses.

Our major findings are as follows:

- Among QMB-eligible seniors, the probability and intensity of Part B Medicare use are significantly higher among those enrolled in QMB than among those not enrolled.

- The probability of having any Medicare Part B utilization is 12 percentage points higher among individuals enrolled in QMB than among eligible non-enrollees. Among elderly Medicare beneficiaries that have any Part B use, Part B expenditures are 44% higher for those enrolled in QMB than for individuals who are not enrolled.

- The probability of having any Medicare Part A expenses is eight percentage points higher among QMBs than among eligible non-enrollees. However, there is no difference between these two groups in Part A expenditures for those who have any Part A charges.

- On average, QMB enrollees spend $1,900 more per year on health services covered by Medicare Part B and $1,300 more per year on Medicare Part A services than do eligible non-enrollees. Only 20 percent of the increase in Part B expenditures and about 100 percent of the increase in Part A use is attributable to a higher probability of use.

For every 5% increase in proportion of the QMB-eligible population enrolled in the program, there is a $300 million increase in Part A expenditures and a $443 million increase in Part B expenditures. Thus, we estimate the current financial impact of the QMB program (assuming an enrollment rate of 45%) to be $6.7 billion per year in 1993 dollars. If 100% of the eligible population were enrolled in the QMB program, the program's financial impact could reach $14.9 billion. This represents an upper-bound estimate, however, because individuals in the poorest health have already enrolled in the program (Neumann, Bernardin, Bayer, & Evans, 1994).

In summary, our analysis demonstrates that the QMB program has achieved its goal of improving access to medical care for low-income elderly Medicare beneficiaries. It is clear that individuals enrolled in QMB are utilizing its benefits. Additional research is needed to determine whether differences in expenditures among QMBs and eligible non-enrollees can be attributed to adverse selection into the program.

CHAPTER 1

INTRODUCTION

Since the Qualified Medicare Beneficiary (QMB) program was implemented in 1990, state Medicaid programs have been required to pay the Medicare premiums, deductibles, and copayments for elderly and disabled Medicare beneficiaries with incomes at or below the federal poverty level (FPL) and assets not exceeding twice the resource limits for Supplemental Security Income (SSI). Congress designed the QMB program to protect low-income beneficiaries from some of the burdens of Medicare out-of-pocket costs.

This study's purpose is to compare the health expenditures of the QMB enrolled population with those of elderly Medicare beneficiaries who are eligible for but not enrolled in the program. Specifically, the study addressed three research questions:

1) Is the health care utilization of QMB enrollees significantly different from that of eligible non-enrollees? If so, are differences specific to Medicare Part A or Part B services?

2) Is there evidence of adverse selection with respect to enrollment in the QMB program?[1]

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[1] In the health economics literature, "adverse selection" traditionally is defined as an individual's decision to obtain health insurance coverage based on knowledge that he or she will incur large health care expenses. In this paper, we use a broader definition of adverse selection to reflect the characteristics of the QMB population. As reported by Neumann et al. (1994), many of the elderly enrolled in the QMB program do not know that they are enrolled and, in fact, reported on the QMB supplement to the MCBS that they had never heard of the program. Therefore, in this paper, we

3) What is the impact of QMB enrollment on Medicare expenditures?

To answer these questions, we analyzed data from the Medicare Current Beneficiary Survey (MCBS) and the MCBS National Claims History File.

In Chapter Two of this report, we provide a brief history of the QMB program, and we review recent findings on differences in beneficiary characteristics between QMB enrollees and eligible Medicare beneficiaries who are not enrolled in the program. In Chapter Three, we describe databases used for this study and characteristics of the study population. In Chapter Four, we outline the econometric methods used to determine the impact of QMB participation on health care utilization, and we present our findings. In Chapter Five, we summarize key findings, and in Chapter Six, we discuss the implications of these results. The final chapter suggests areas for future research.

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define "adverse selection" as a decision made by a QMB-eligible beneficiary *or the beneficiary's agent* (e.g., a family member, hospital social worker, legal aid staff, or outreach volunteers) to enroll the beneficiary in QMB based on anticipation that he or she will incur large health care expenses.

CHAPTER 2

BACKGROUND

The Medicare program's cost-sharing provisions -- its premiums, deductibles, and copayments -- can present a substantial financial hardship for low-income beneficiaries. To alleviate some of this burden, Congress enacted the Qualified Medicare Beneficiary program, which requires state Medicaid programs to pay Medicare cost-sharing amounts for low-income Medicare beneficiaries.

States have always had the option to pay the Medicare premiums and deductibles for beneficiaries who qualify for Medicaid. Since 1990, federal law has required state Medicaid programs to pay the cost-sharing provisions for all Medicare beneficiaries whose incomes do not exceed 100 percent of the federal poverty level (FPL)[2] and whose resources do not exceed twice the amount established for Supplemental Security Income (SSI) eligibility.[3] Individuals who meet these criteria are termed "Qualified Medicare Beneficiaries" (QMBs). Since the program began in 1990, policymakers and advocates for the elderly have been concerned about low program participation.

Despite attempts by many public and private organizations to inform eligible seniors about the benefits, more than half of eligible individuals are not participating in the program.

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[2]In 1992, the FPL was $7,143 for singles and $9,137 for married couples.

[3]In 1992, the asset threshold was $4,000 for singles and $6,000 for couples.

A study by Families USA (1992) reported that approximately 2 million of the 4.2 million eligible seniors were not enrolled. A subsequent report by the General Accounting Office (1994) confirmed the general accuracy of this estimate. Anecdotal reports indicate that some states have not aggressively enrolled eligible individuals, in part because they would rather pay for needed services through the Medicaid program.

A recent study by Neumann et al. (1994) analyzed barriers to enrollment in the QMB program. The authors reached three general conclusions: First, the program is not serving many individuals for whom it was intended. Well over 2 million eligible elderly beneficiaries are not participating, and participation remains low even among truly needy individuals. Over 50 percent of those reporting incomes under $1,000 and over 50 percent of those with at least one hospital visit over the previous year-and-a-half do not participate. The data also suggest that a number of eligible beneficiaries are purchasing supplemental insurance coverage, despite the fact that the QMB program was designed to cover most of their out-of-pocket health costs.

Second, beneficiaries who are enrolled as QMBs tend to be those most in need of the program. Beneficiaries enrolled in other government assistance programs, for example, are very likely to participate in the QMB program. Among QMB-eligibles, the two subgroups most vulnerable to Medicare out-of-pocket costs -- lower income beneficiaries and those with poorer health status -- are more likely to enroll in QMB than are upper-income seniors and those in good or excellent health. Participation is also higher among African Americans and

Hispanics, those with less education, and those reporting few social contacts (e.g., those reporting no contacts with friends or family members during the previous two weeks; widowed, divorced, or never married individuals; and geographically isolated beneficiaries). Those residing in rural areas and those living far from their usual source of care have higher participation rates (Neumann et al., 1994).

The third finding to emerge from Neumann et al.'s (1994) study was that most eligible beneficiaries are ill-informed about the QMB program. Only 7 percent of eligibles have ever heard of the program; of the 93 percent who have *not* heard of the program, almost 40 percent are actually enrolled. Among nonparticipants, the most frequently provided reasons for not enrolling were that they did not believe they needed the program (33 percent), they did not think they qualified (27 percent), or they were not aware of the program (16 percent).

Based on these findings, Neumann et al. (1994) suggested several areas for future research. Among these, they recommended an analysis that would link information from QMB enrollment data with data on utilization and expenditures of QMB participants and eligible non-enrollees. Such an analysis, they noted, would provide a more complete profile of the health care experiences of QMB eligibles and would make it possible to compare the experiences of enrollees and non-enrollees. These recommendations provided the basis for the current study.

CHAPTER 3

DATA

3.1 Database Development

To complete this analysis, we analyzed data from the Medicare Current Beneficiary Survey (MCBS). The MCBS, sponsored by the Health Care Financing Administration, is an ongoing survey that examines the current status of the Medicare population (Adler, 1994). The survey consists of a series of interviews conducted three times a year with a stratified random sample of approximately 12,000 elderly and non-elderly Medicare beneficiaries. Questions focus on their health care utilization; expenditures; health status; family support; living arrangements, and financial resources.

We analyzed three components of the MCBS, as follows:

- ***The 1992 Income and Assets (I&A) Supplement:*** The I&A Supplement collects detailed information about beneficiaries' financial resources, including sources of income and assets. We identified respondents as QMB-eligible if their incomes did not exceed 100 percent of the federal poverty level, and their assets did not exceed twice the amount established for SSI eligibility.

- ***The QMB Supplement:*** In the spring of 1993, this questionnaire was administered to the sample of MCBS respondents identified as being eligible for the QMB program. The questionnaire was designed to examine beneficiaries' knowledge of the QMB program, their sources of information, and, for nonenrollees, their reasons for not participating.

- *The National Claims History File (NCHF):* The NCHF contains inpatient and outpatient utilization and financial data on all MCBS respondents, including: provider charges, Medicare reimbursement, as well the deductibles and copayments associated with a specific service.

From these MCBS databases, we created a set of analytic files. First, we used the MCBS to identify a sample of elderly, noninstitutionalized beneficiaries who met the eligibility criteria for the QMB program. Next, we merged data from the QMB supplement with two other databases containing information on our sample of QMB-eligibles -- one incorporating data from the MCBS core survey on characteristics of the eligible population -- and the other containing information from HCFA's 1993 Medicare "Buy-In" File, which was used to determine whether eligible beneficiaries were actually enrolled in the program.

The comprehensive QMB population databases described above were then merged with NCHF-derived health care use and expenditure summary files. This portion of the analysis required pre-processing the institutional (e.g., hospital inpatient and outpatient) and non-institutional (e.g. physician and medical suppliers) claims files available as part of the MCBS database. We analyzed claims for services provided during calendar year 1993 (e.g., for dates of service 1/1/93 through 12/31/93). During the pre-processing steps, we removed any transaction or adjudication records that did not record as actual health service use. This pre-processing procedure closely followed the NCHF analytic file creation strategy outlined by Parente et al. (1995). Using only the data elements necessary for the analysis, we generated a resource-use analytic file that summarized each beneficiary's Part A and Part B service use and expenditures, as well as the copayment and deductible amounts paid. This resource-use profile summarized the utilization history of all beneficiaries in the MCBS study population, regardless of QMB participation or eligibility.

3.2 Characteristics of the Study Population

Descriptive statistics for the important variables in our sample are presented in Table 1. We report means and standard deviations for the entire sample, as well as for those samples of QMB eligibles enrolled and not enrolled in the program. Throughout this report, we provide unweighted statistics, because use of the sample weights would have unnecessarily complicated the analysis. We note, however, that use of sample weights in a sensitivity analysis led to no appreciable change in results. This result is not surprising, as many of the variables on which the sample was stratified (e.g., race) were entered as co-variates in our models.

As indicated in Table 1, the vast majority of QMB-eligible seniors are women, and the average age of respondents is 77. The average respondent has only eight years of education, and average self-reported income is slightly over $1,000 per year . As Neumann et al. (1994) noted, the income variable most likely reflects substantial measurement error.

In this sample, only 43 percent of eligible adults are enrolled in the QMB program. This estimate is extremely close to the weighted mean of 44 percent reported in Neumann et al. (1994). In the last two columns of the table, we report sample characteristics by QMB

Table 1
Variable Definitions and Sample Characteristics

		Means and Standard Deviations		
			QMB enrollment	
Variable Name	Definition	Full Sample	Yes	No
QMB enrollment	Indicator variable, =1 if enrolled in QMB, =0 otherwise.	0.43 (0.50)	1.00 (0.00)	0.00 (0.00)
Female	Indicator variable, =1 if respondent is female, =0 otherwise.	0.74 (0.44)	0.78 (0.42)	0.71 (0.45)
Male	Indicator variable, =1 if respondent is male, =0 otherwise.	0.26 (0.44)	0.22 (0.42)	0.29 (0.45)
Black	Indicator variable, =1 if respondent is Black, =0 otherwise.	0.24 (0.43)	0.32 (0.47)	0.19 (0.40)
Hispanic	Indicator variable, =1 if respondent is Hispanic, =0 otherwise.	0.10 (0.30)	0.12 (0.33)	0.09 (0.28)
White	Indicator variable, =1 if respondent is White, non-Hispanic, =0 otherwise.	0.66 (0.47)	0.56 (0.50)	0.73 (0.45)
Income	Yearly family income.	1269 (1730)	1177 (1721)	1339 (1735)
Age	Age in years.	77.5 (7.81)	77.6 (7.89)	77.4 (7.77)
Education	Years of education.	8.25 (3.70)	7.34 (3.57)	8.94 (3.75)
Own Home	Indicator variable, =1 if respondent owns home, =0 otherwise.	0.43 (0.50)	0.27 (0.44)	0.55 (0.50)
Rent Home	Indicator variable, =1 if respondent rents home, =0 otherwise.	0.32 (0.47)	0.44 (0.50)	0.23 (0.42)
Live with others	Indicator variable, =1 if respondent lives in someone else's home, =0 otherwise.	0.25 (0.43)	0.29 (0.45)	0.22 (0.42)
Excellent/Very Good Health	Indicator variable, =1 if respondent is in excellent or very good health, =0 otherwise.	0.30 (0.46)	0.23 (0.42)	0.37 (0.48)
Good Health	Indicator variable, =1 if respondent is in good health, =0 otherwise.	0.27 (0.44)	0.25 (0.44)	0.27 (0.45)
Fair/Poor Health	Indicator variable, =1 if respondent is in fair or poor health, =0 otherwise.	0.43 (0.50)	0.51 (0.50)	0.37 (0.48)
ADL's	Number of reported restrictions on activities of daily living.	0.42 (1.07)	0.60 (1.24)	0.29 (0.90)

Any Part B MD charges	Indicator variable, =1 if respondent had any Part B charges for doctor services, =0 otherwise.	0.78 (0.42)	0.85 (0.36)	0.72 (0.45)
Any Part B charges	Indicator variable, =1 if respondent had any Part B charges, =0 otherwise.	0.78 (0.41)	0.86 (0.35)	0.72 (0.45)
Any Part A charges	Indicator variable, =1 if respondent had any Part A charges, =0 otherwise.	0.20 (0.40)	0.24 (0.43)	0.16 (0.37)
Part B MD charges	Total Part B charges for doctor services, given positive charges.	2964 (5713)	3378 (4882)	2592 (6347)
Part B Charges	Total Part B charges, given positive charges.	3967 (7229)	4549 (6559)	3444 (7752)
Part A Charges	Total Part A charges, given positive charges.	16065 (21476)	16023 (16483)	16101 (29065)
Number of observations		1400	605	795

enrollment. These numbers are consistent with the conclusions of Neumann et al., who found that although most eligible seniors do not enroll in the QMB program, those most in need are the most likely to enroll. Eligible beneficiaries enrolled in QMB have lower incomes, lower rates of home ownership, and higher reported activities of daily living (ADL) deficiencies than those not enrolled. In addition, QMBs are less likely to report excellent or very good health and more likely to report fair or poor health than are eligible non-enrollees.

In last few rows of the table, we report six measures of health care utilization. First, we present the proportion of respondents with any Medicare Part B charges for doctor visits; any Part B charges (e.g., outpatient hospital encounters); and any Part A charges. Next, we report mean expenditures for beneficiaries who used any type of health service. These results indicate that both the probability and intensity of use are significantly higher for QMBs than for Medicare beneficiaries who are eligible for but not enrolled in the QMB program. To provide some indication of the magnitude of these differences, in Table 2, we report simple differences in means for all three probability and intensity-of-use measures. For this table, we calculated the mean of log expenditures, because this difference is equivalent to a percentage difference in use.

The results reported in Table 2 indicate that among QMB eligibles, the probability of having any Part B charges is 13.1 percent higher for those enrolled in the program than for those not enrolled, and the probability of having any Part A charges is 8.1 percentage points higher for QMBs than for eligible non-enrollees. Similarly, among QMB eligibles with

Table 2
Measures of Health Care Use
by QMB Enrollment

Means and Standard Errors

Variable	QMB Enrollment Yes (1)	QMB Enrollment No (2)	Difference (1) - (2)
Access to care measures:			
Any MD charges	0.848	0.721	0.127
	(0.015)	(0.016)	(0.022)
Any Part B charges	0.856	0.725	0.131
	(0.014)	(0.016)	(0.021)
Any Part A charges	0.243	0.162	0.081
	(0.017)	(0.013)	(0.022)
Intensity of use measures:			
ln(MD Charges)	7.243	6.746	0.497
	(0.063)	(0.065)	(0.091)
ln(Part B charges)	7.523	7.012	0.511
	(0.064)	(0.068)	(0.093)
ln(Part A charges)	9.228	9.126	0.102
	(0.079)	(0.090)	(0.120)

positive expenditures in a particular service category, the Part B expenses of QMB enrollees are 51.1 percent higher than those of eligible beneficiaries not participating in the program, and Part A expenses of QMBs are 10.2 percent higher than those of eligible non-enrollees. All differences except the differences in Part A expenses are precisely estimated, and we can easily reject the null hypothesis that the differences in means are zero.

In the following section, we provide a more detailed analysis of the impact of QMB enrollment on health care utilization. Because QMB enrollees have very different demographic and health characteristics than those not enrolled in the program, we first estimate a multivariate model that controls for differences among Medicare beneficiaries. Next, we consider whether QMB's estimated impact on utilization represents a causal relationship or a simple correlation. As noted in Table 1, those in the poorest health -- who thus can be expected to have higher rates of health care utilization -- are also more likely to enroll in QMB. If people who anticipate having large medical expenses (or whose agents anticipate that they will have large medical expenses) are the most likely to enroll in QMB, the differences in use between enrolled and non-enrolled seniors reported in Table 2 would overstate the causal impact of enrollment on use. In Chapter 4, we outline a multi-equation system designed to eliminate the potential bias generated by this type of adverse selection.

CHAPTER 4

METHODS and RESULTS

4.1 Introduction

To determine the impact of QMB enrollment on medical use, we use a two-part model of demand (Manning et al., 1987) in which the decision to use medical services and the intensity of service utilization are modeled separately. We have modeled the probability-of-use equation as a simple probit and estimated the log-of-positive-expenditures equation by ordinary least-squares (OLS). Our two-part model is substantially more complex than previous applications of the two-part model of demand, because we suspect that one important covariate, QMB enrollment, may be endogenous. In the next section, we present a standard two-part model of medical care use assuming all covariates in the model are exogenous. We then discuss the results from this exercise. In the final section, we present a multi-equation system designed to provide unbiased estimates of QMB enrollment, accounting for adverse selection. Estimating these systems appropriately requires identification of a factor correlated with QMB enrollment but uncorrelated with the probability or intensity of medical care use.

4.2 A Standard Two-Part Model of Demand

As we noted above, we used the Medicare claims history files to generate three primary measures of health care use for the QMB-eligible population: use of Part B physician services; use of any Part B services; and use of Part A services. All three variables have similar sample characteristics in that a proportion of the population does not use the services, and the distribution of positive expenses is highly skewed. For this class of variables, the standard econometric model is the two-part model of demand. The first equation in the system models factors determining whether a senior has any medical care use, and the second equation models determinants of intensity of use when any use has been observed.

To model the probability of receiving a particular type of care (Part A or Part B covered services), we use a simple probit model. In the model for Part B expenditures, let indicator variable $Y_i = 1$ if individual i has any Part B charges, and let $Y_i = 0$ otherwise. The choice problem is described by the latent variable model,

$$(1) \quad Y_i^* = X_i\beta_1 + QMB_i\delta + \epsilon_{1i}$$

where Y_i^* is the net benefit an individual receives from having positive Part B expenses; X_i is a vector of individual characteristics; QMB_i is an indicator variable that equals 1 if the respondent is enrolled in QMB and 0 otherwise; and ϵ_{1i} is a normally distributed random error with zero mean and unit variance. Individuals will only use medical services if the expected net benefits are positive; thus the probability of observing part B expenses is defined as

$$(2) \quad \mathrm{Prob}[Y_i = 1] = \mathrm{Prob}[X_i\beta_1 + QMB_i\delta + \epsilon_{1i} > 0] = \Phi[X_i\beta_1 + QMB_i\delta]$$

where $\Phi()$ is the evaluation of the standard normal cdf.

Because the probability of use is a nonlinear function of the parameters β_1 and δ, we cannot directly measure the impact of QMB enrollment on use by the magnitude of the parameter δ. With coefficients from the probit model, we calculate two additional variables to measure the qualitative importance of QMB enrollment on the probability of use. The first variable is defined as the "marginal effect," and it measures the change in probability of use given QMB enrollment. Mathematically, the marginal effect is defined as $\partial \text{Prob}(Y_i = 1) / \partial \text{QMB}_i = \delta\, \phi(X_i\beta_1)$, where $\phi()$ is the evaluation of the standard normal pdf. The value of the marginal effect will be determined in part by the assumed probability of use without QMB. In this instance, we calculate the marginal effect for a person with an average probability of use, where if μ is the sample mean of the dependent variable (0.78 in the case of part B charges), the marginal effect can be calculated as $\delta\phi(z)$ where $z=\Phi^{-1}(\mu)$. The second variable that measures the impact of QMB enrollment on use is defined as the "average treatment effect," which is the average difference between the probability that a beneficiary would have Part B expenses if he/she were enrolled in QMB. If n is the sample size and $\hat{\beta}_1$ and $\hat{\delta}$ are the maximum likelihood estimates of the parameters in equation (2), the average treatment effect equals $(1/n)\Sigma_i\, [\Phi(X_i\hat{\beta}_1 + \hat{\delta}) - \Phi(X_i\hat{\beta}_1)]$. In most applications, the marginal effect and average treatment effect give very similar results. We use the "delta" method to calculate the variance of the marginal and average treatment effects.

In the second part of the two-part demand model, we control for the skewness in medical demand by estimating with ordinary-least squares the determinants of log expenditures. Using the notation established above, the equation we estimate is of the form

$$(3) \qquad \ln(E_i) = X_i\beta_2 + QMB_i\alpha + \epsilon_{2i} \qquad for\ E_i>0$$

where X is the same set of covariates used in the probit model above, and ϵ_{2i} is a zero mean random error with $Var(\epsilon_{2i})=\sigma^2_2$. Because log expenditures are linear in QMB enrollment, the primary parameter of interest, α, measures the percentage increase in medical expenses (given that any have occurred) attributable to QMB enrollment.

Two-part demand estimates for the QMB enrollment indicator variable are reported in Table 3. In all of these models, we use the following covariates: age and age square; log income; measures of self-reported health status; counts of ADLs; and indicator variables for gender, race, education, home ownership status, region of the country, and urbanicity. To shorten the exposition, the coefficients for these additional variables are not reported here.

As the R^2 's in Table 3 indicate, these controls explain little of the sample variation in the probability and intensity of use. Only the self-reported measures of health status and counts of ADLs are uniformly statistically significant across models. The fact that there is little variation in demographic characteristics is not surprising in light of the highly selective nature of the sample. The QMB-eligible population is, on average, very poor, very old, and has a low level of educational attainment. Although these demographic variables typically

Table 3
Two-Part Model Estimates,
Impact of QMB Enrollment on Health Care Use

Parameter Estimates and Standard Errors

	Part B MD charges		Part B charges		Part A Charges	
Variable	Probit model, any use	OLS model, log use	Probit model, any use	OLS model, log use	Probit model, any use	OLS model, log use
QMB Enrollment	0.474 (0.092)	0.474 (0.103)	0.455 (0.091)	0.441 (0.106)	0.292 (0.090)	0.025 (0.132)
Marginal Effect of *QMB enrollment*	0.142 (0.027)		0.146 (0.027)		0.083 (0.025)	
Average Treatment Effect *QMB enrollment*	0.125 (0.023)		0.123 (0.024)		0.079 (0.025)	
mean of dependent variable	0.776	6.981	0.781	7.254	0.197	9.180
number of observations	1400	1086	1400	1093	1400	276
R^2		0.081		0.081		0.141
-2 log likelihood	1378.3		1350.6		1328.6	

The marginal effects, $\partial Prob/\partial X$, represents the change in the probability of use given QMB enrollment. If β_{qmb} is the probit coefficient on the QMB variable, and μ is the sample mean of the dependent variable, the marginal effect is calculated as $\phi(z)\beta_{qmb}$ where $z=\Phi^{-1}(\mu)$. The average treatment effects represent the average change in the probability of use generated by QMB enrollment.

All models include the following list of covariates: age, age squared, log income, and counts of ADL's, plus indicators for whether the respondent is black, hispanic, female, married, widowed respondents, in excellent health, in good health, owns their home, rents their home, has less than 7 years of education, has 7-8 years of school, has 9-11 years of school, has 12 years of school, has 1-2 living children, has 3-5 living children, has 6 or more living children, whether the respondent lives in the south, west, or midwest, and whether the respondent lives in a metropolitan area.

can explain some of the cross-sectional variability in probability and intensity of use, once the sample has been selected to include only QMB eligibles, these three variables have little explanatory power.

The probit equations indicate that on average, the probability of having any Part B charges is 12.5 percentage points higher among QMBs than among Medicare beneficiaries eligible for but not enrolled in the QMB program. The probability of having any Part A charges is 7.9 percentage points higher for beneficiaries enrolled in the QMB program than for eligible non-enrollees. Similarly, among beneficiaries with any Part B expenses, the Part B expenditures of QMB enrollees are 44.1 percent higher than those of eligible seniors not participating in the program. Interestingly, the coefficients on the QMB indicator variable from the multi-variate, two-part demand model are nearly identical to the simple difference in mean calculations reported in Table 2.

If we interpret the coefficients on the QMB variables from the two-part model as the "causal" impact of enrollment on utilization, we can perform a simple simulation to estimate the average per-person change in use attributable to QMB enrollment. This simulation is conducted as follows: Let the variables $\hat{\delta}$, $\hat{\beta}_1$, $\hat{\alpha}$, and $\hat{\beta}_2$ represent parameter estimates from the two-part demand model for a particular expenditure category. For any individual i, the predicted probability of use is defined as $\Phi(X_i\hat{\beta}_1 + QMB_i\ \hat{\delta},)$, and following Manning et al. (1987), predicted intensity of expenditures is $\hat{\gamma}\exp(X_i\hat{\beta}_2+QMB_i\hat{\alpha})$. The variable $\hat{\gamma}$ is the "smearing" estimate of Duan (1983), making it possible to transform predictions from a model with logged dependent variables back into a linear scale. To calculate this value, we note that predicted residuals from the log expenditures equation are $\hat{\epsilon}_{2i}=\ln(E_i/E_i>0) - X_i\hat{\beta}_2 - QMB_i\hat{\alpha}$, and therefore $\hat{\gamma} = (1/n_1)\Sigma_i\exp(\hat{\epsilon}_{2i})$, where n_1 is the number of observatic..s in the data set with positive expenses. Using these values, the predicted expenses for individual i are simply $\Phi(X_i\hat{\beta}_1 + QMB_i\,\hat{\delta},)\hat{\gamma}\exp(X_i\hat{\beta}_2+QMB_i\hat{\alpha})$. To estimate the average impact of QMB on utilization, we use a measure similar to the average treatment effect discussed above. First, we calculate predicted use for all people assuming they were enrolled in the program. This value is by definition $\Phi(X_i\hat{\beta}_1 + \hat{\delta},)\hat{\gamma}\exp(X_i\hat{\beta}_2+\hat{\alpha})$. Next, we calculate predicted use assuming no QMB program; this is defined as $\Phi(X_i\hat{\beta}_1\,)\hat{\gamma}\exp(X_i\hat{\beta}_2)]$. The average difference between these two quantities, $\Delta = (1/n)\Sigma_i\,[\,\Phi(X_i\hat{\beta}_1 + \hat{\delta},)\hat{\gamma}\exp(X_i\hat{\beta}_2+\hat{\alpha}) - \Phi(X_i\hat{\beta}_1\,)\hat{\gamma}\exp(X_i\hat{\beta}_2)]]$, is the average change in expenditures attributable to QMB enrollment.

Results from this simulation are reported in Table 4. On average, QMB enrollment is associated with annual per-person Part B expenditures of $1,918 and annual per-person Part A charges of $1,326. This finding is consistent with expected utilization patterns under current Part A and Part B cost-sharing requirements. Beneficiaries requiring hospitalization often must pay their Part A deductible during their first admission. Part B services (unless linked with a hospitalization) typically are more discretionary than those covered by Part A. Beneficiaries generally can choose whether they truly need a Part B service or wish to pay the deductible to obtain it. Low-income beneficiaries may decide to forego discretionary Part B services. Because the QMB program substantially reduces the financial burden of Part B services, QMB enrollees (all of whom have low incomes) can be expected to use these

Table 4
Two-Part Model Estimates,
Impact of QMB Enrollment on Average Expenditures

	Part B MD charges	All Part B charges	All Part A charges
Predicted change in per person expenditures attributable to QMB enrollment	$1490	$1918	$1326

services at a significantly higher level than would Medicare beneficiaries who are eligible for but not enrolled in the QMB program. Thus, the increase in Medicare expenditures associated with QMB enrollment should be greater for Part B services than for Part A services. Approximately 20% of the predicted increase in expenditures is attributable to the higher probability of use for QMB enrollees, and 80 percent of the increase is attributable to the change in intensity of use. Nearly all of the increase in Part A expenses can be attributed to the increased probability of use.

4.3 Controlling for Adverse Selection

The two-part model outlined above provides unbiased estimates of the impact of QMB enrollment on medical care use if QMB enrollment is not correlated with a person's unobserved propensity to use medical care. Stated differently, the estimates will be unbiased if beneficiaries' enrollment in QMB is unrelated to their expected medical care use. If, however, those who anticipate having large medical expenses or those who have the most contact with health providers are the most likely to enroll in QMB, the two-part estimates described above will greatly overstate the impact of the QMB program. Is this a likely scenario? As results in Table 1 indicate, beneficiaries with the poorest self-reported health status and those with the higher reported ADL deficiencies are the most likely to enroll in the program. The average ADL deficiency for QMBs is 0.6 but only 0.29 for eligible beneficiaries who are not enrolled. Similarly, the proportion of the QMB population reporting excellent/very good health is only 0.23, whereas the corresponding proportion for eligible non-enrollees is 0.37. In general, those who could be expected to have higher medical expenses are indeed the most likely to enroll in the QMB program. These results suggest that QMB enrollment is not random, but rather, is subject to adverse selection.

To correct the two-part estimates for bias introduced by the potential non-random assignment of seniors into the QMB program, we must first model the decision to enroll in QMB. Suppose we can monetize the benefits of QMB enrollment, and assume we can write the net benefits of enrolling (QMB_i^*) as a function of observed and unobserved characteristics

$$(4) \quad QMB_i^* = Z_i\gamma + \epsilon_{3i}$$

where Z_i is a vector of observable demographic characteristics and ϵ_{3i} is a zero mean, unit variance, normally distributed random error. An individual will enroll in QMB if the net benefits are positive, i.e., if $QMB_i^* > 0$. To allow for possible adverse selection into the program, we assume that the decision to enroll is correlated with the decision to use services and with the intensity of use. Statistically, this can be accomplished by assuming that the unobserved components in the three equations are correlated. Specifically, we assume ϵ_{1i}, ϵ_{2i} and ϵ_{3i} are distributed as a multivariate normal, where all three variables have zero expected variances as specified above, but $\mathrm{cov}[\epsilon_{1i},\epsilon_{3i}] = \rho_{13}$ and $\mathrm{cov}[\epsilon_{2i},\epsilon_{3i}] = \rho_{23}\sigma_2$.

Because the decision to enroll and the decision to use medical services are now assumed to be correlated, we must estimate these equations jointly. In our analysis, we will estimate two separate systems. First, we estimate the enrollment and use equations, and next, we jointly estimate the enrollment and intensity of use equations. We could estimate a three-equation system (use, intensity of use, and enrollment equation), but this would require modeling the covariance between the probability-of-use and intensity-of-use equations. This covariance can only be identified if we can identify a variable that affects intensity of use but not probability of use. Because we do not believe it would be possible to identify such a variable, we assume that the two errors are uncorrelated and that the use and intensity of use equations are independent. This assumption allows us to estimate two systems of equations instead of estimating one three-equation system.

Because both the decision to use services and the decision to enroll in the QMB program are dichotomous, there are four possible states ($Y_i = 0$, $QMB_i=0$; $Y_i = 0$, $QMB_i=1$; $Y_i = 1$, $QMB_i=0$; and $Y_i = 1$, $QMB_i=1$). Modeling either the use or the enrollment equation separately can be accomplished through simple probit models. Given the assumed correlation between these two decisions, however, the likelihood function corresponding to this set of events is a bivariate probit. In this system of equations, we estimate the probability of an elderly beneficiary being in one of the four categories listed above.

In light of the potential correlation between the intensity of use and QMB enrollment decisions, single-equation estimates of equation (3) will capture not only the impact of QMB enrollment on use, but also the fact that people with higher anticipated expenses are more likely to enroll in the program. Because the potentially endogenous covariate is discrete

(QMB enrollment), controlling for adverse selection cannot be accomplished with a standard model such as two-stage least-square (2SLS). Instead, we draw from the large literature on bias introduced by sample selection to produce a model that controls for nonrandom selection into the treatment group. Specifically, because we assume that QMB enrollment and intensity of use are correlated, the expected value of the error term in the use equation, ϵ_{2i} is now correlated with QMB enrollment, thereby violating the primary assumption of ordinary least-square models. In this instance, it is not difficult to show that expected log use is

$$(5)\quad E[\ln[E_i] \mid QMB_i] = X_i\beta_2 + \alpha\ QMB_i + E[\epsilon_{2i} \mid QMB_i]$$

$$= X_i\beta_2 + \alpha\ QMB_i + \rho_{23}\sigma_2\left(QMB_i\ \frac{\phi[Z_i\gamma]}{\Phi[Z_i\gamma]} - (1-QMB_i)\ \frac{\phi[Z_i\gamma]}{1-\Phi[Z_i\gamma]}\right)$$

$$= X_i\beta_2 + \alpha\ QMB_i + \rho_{23}\sigma_2 H_i$$

where ϕ and Φ are evaluations of the standard normal pdf and cdf respectively, and by definition, $\Phi[Z_i\gamma]$ is the probability a beneficiary will enroll in the QMB program. The variable H is the sample selection correction term representing the size of bias associated with adverse selection into the QMB program. As equation (5) indicates, if $\rho_{23} = 0$, then OLS estimates of equation (3) will provide an unbiased estimate of the effect of QMB on use. However, if $\rho_{23} > 0$ ($\rho_{23} < 0$), then OLS estimates of (3) will over- (under-) estimate α.

The sample selection correction term H is a simple omitted variable that introduces a bias into an OLS equation. To eliminate the bias, we use a two-step procedure outlined in

Barnow et al. (1981) and Lalonde (1986). The two-step procedure first produces an estimate of the omitted factor H; then the log use equation is re-estimated with the omitted factor replaced. First, we estimate a reduced-form probit model of program enrollment to obtain estimates of $\hat{\gamma}$. Using these values, we construct an estimate of sample selection term H and include this as an independent variable in the expenditure equation. The second-stage model is then of the form

$$(6)\quad \ln[E_i] = X_i\beta_2 + \alpha QMB_i + \theta\hat{H}_i + \mu_i$$

where μ_i is a random error and the coefficient α is an estimate of the product $\rho_{23}\sigma_2$. Because μ_i is heteroskedastic and we utilize estimates of the sample selection correction term $\hat{H}$ rather than actual values, OLS estimates of standard errors are inconsistent. Accordingly, we estimate corrected standard errors using procedures suggested by Heckman (1978, 1979) and Greene (1981).

In practice, the vector Z in the QMB enrollment equation will include all covariates used in the probability-of-use equation. The bivariate probit model outlined above can be estimated if there is at least one variable determining QMB enrollment that is uncorrelated with an individual's propensity to use services. In the best of all possible worlds, these variables, called instruments, will mimic a random selection device, giving people different probabilities of enrollment that are uncorrelated with their probability of use. We have identified two potential instruments that we believe fit this definition. The first is the percent of a state's Medicaid population who are elderly. The second is the number of outreach programs states have used to inform seniors about the QMB program.

Elderly Medicare beneficiaries must apply for the QMB program at state Medicaid offices. Seniors represent a small proportion of the Medicaid population, accounting for about 12 percent of all recipients nationwide in 1992. There is, however, tremendous variation among states in the proportion of Medicaid recipients who are elderly. Because some state Medicaid offices may have more experience serving the elderly population, we suspect that seniors are more likely to enroll in QMB if they comprise a larger portion of a state's Medicaid population. Similarly, a large elderly Medicaid population may signal a state's commitment to providing care for the elderly. Likewise, we suspect that seniors in states with more aggressive QMB outreach programs will have a higher probability of enrollment. As noted in the introduction, about half of the elderly Medicare beneficiaries eligible for QMB have not enrolled in the program.

Since the beginning of the QMB program, many public and private organizations have conducted outreach programs to inform seniors about QMB and to facilitate the enrollment process. In a review of these programs, the American Public Welfare Association (1993) identified seven types of outreach programs based on the channel of communication used. These included: mass mailings; public service announcements; press releases; brochures; outstationing (providing opportunities to apply for the program in community settings, outside the Medicaid office); working with aging networks; and working with community organizations. Neumann et al. (1994) demonstrated that although QMB enrollment was not correlated with any particular outreach program, enrollment probabilities were higher in states that adopted several outreach strategies. Therefore, we use the number of outreach strategies (0-7) as an instrument for enrollment. Although QMB enrollment is correlated with the number of state outreach programs and the proportion of a state's Medicaid population who are elderly, we do not expect these variables to be correlated with either probability or intensity of use.

In Table 5, we report coefficients on the two instruments generated from probit models predicting the probability of QMB enrollment. Other covariates in the model include those used in the two-part demand equations. In these models, elderly Medicare beneficiaries in states with several outreach programs or states with a larger proportion of Medicaid recipients age 65 and older are more likely to enroll in the program. For example, if the proportion of elderly Medicaid recipient increases by one percentage point, the probability of enrollment increases by 2.8 percentage points. In the final model, the probit estimates suggest that the addition on one more outreach program increases the probability of enrollment by three percentage points. The estimated coefficients reported in Table 5 are all statistically significant.

In Table 6, we report results from the bivariate probit models where we jointly estimate the decision to use medical care and to enroll in QMB. We estimate models for both Part B and Part A expenses. For each expenditure type, we report four models. First,

Table 5
Probit Estimates of QMB Enrollment Equation

Parameter Estimates and Standard Errors

	Model (1)		Model (2)		Model (3)	
Independent Variable	Probit Estimates	Marginal Effects	Probit Estimates	Marginal Effects	Probit Estimates	Marginal Effects
% Medicaid Population that is elderly	0.071 (0.014)	0.028 (0.004)	0.345 (0.057)	0.137 (0.022)	0.066 (0.014)	0.026 (0.005)
% Medicaid Population that is elderly squared			-1.319 (0.250)	0.519 (0.098)		
# of state-run QMB outreach programs					0.077 (0.024)	0.030 (0.009)

Other exogenous variables include those listed in Table 3.

Table 6
Bivariate Probit Estimates
Probability of Use Equations from Two-Part Model

Parameter Estimates and Standard Errors

	Instrument	Bivariate Probit Estimates: Coefficient on QMB enrollment	Bivariate Probit Estimates: Average Treatment Effect	Two-Stage Least-Square Estimates: Coefficient on QMB enrollment	Two-Stage Least-Square Estimates: Specification test statistic
Any Part B Charges					
(1)		0.474 (0.092)	0.125 (0.023)		
(2)	% Medicaid Population that is elderly	0.492 (0.545)	0.129 (0.139)	0.268 (0.175)	
(3)	% Medicaid Population that is elderly, and its square	0.516 (0.391)	0.135 (0.100)	0.196 (0.128)	0.37
(4)	% Medicaid Population that is elderly and # of QMB outreach programs (0-7)	0.579 (0.484)	0.152 (0.123)	0.257 (0.151)	0.02
Any Part A Charges					
(5)		0.292 (0.090)	0.079 (0.025)		
(6)	% Medicaid Population that is elderly	-0.113 (0.518)	-0.030 (0.138)	-0.059 (0.172)	
(7)	% Medicaid Population that is elderly, and it's square	0.034 (0.407)	0.010 (0.109)	0.056 (0.126)	1.02
(8)	% Medicaid Population that is elderly and # of QMB outreach programs (0-7)	0.106 (0.488)	0.029 (0.131)	0.080 (0.147)	2.68

Other exogenous variables include those listed in Table 3. The results in lines (1) and (5) are the single-equation probit estimates reported in table 3. The specification test is distributed as a χ^2 with 1 degree of freedom. The 95 percent critical value for a χ^2 (1) is 3.84.

we report estimates from Table 3 that assumed QMB enrollment was not a function of anticipated medical care use. The final three models use the proportion of Medicaid recipients who are elderly, the square of this number, and the number of state outreach programs as instruments for QMB enrollment. In the bivariate probit models, we report the coefficient on the QMB enrollment variable and the implied average treatment effect.

In the bivariate probit equations modeling Part B usage, the parameter estimates are similar in magnitude to results from the single equation probit models. Unfortunately, the bivariate probit system estimates are imprecisely estimated. There are two possible reasons for this lack of precision: a lack of explanatory power in the first-stage equation that predicts QMB enrollment or an absence of QMB enrollment impact on Medicare Part B use. In light of the similarity between the system and single-equation estimates, we suspect that the former explanation is the more plausible, although we have no way to verify this assertion.

In contrast to the results for Part B use, the bivariate probit estimates for Part A use show no impact of QMB on the probability of use once adverse selection is accounted for. The results in lines 5-7 of Table 6 consistently show a small and imprecise effect of QMB on hospital use.

The last column of Table 6 presents estimates of a somewhat different econometric model. Although the bivariate probit model is straightforward to estimate, the model is substantially more complex than the standard, two-stage least-squares model that one could estimate if all potentially endogenous variables were continuous. Fortunately, Angrist (1991) has shown that instrumental variable estimation is a viable alternative to the bivariate probit model. In the notation of equation (2), Angrist showed in a Monte Carlo study that if we ignore the fact that the dependent variable is dichotomous and estimate

$$(7) \quad Y_i = X_i\beta_1 + QMB_i\delta + \epsilon_{1i}$$

with instrumental variables, the 2SLS estimate of δ is very close to the estimated average treatment effects calculated in a bivariate probit model. We present the standard two-stage least-square results because these models allow us to use standard diagnostic tests to determine whether we have valid instruments. When there are more instruments than endogenous right-hand-side variables in a 2SLS model, we can use Newey's (1985) method of moments specification tests to evaluate the internal consistency of the model, i.e., to determine whether the variables we use as instruments can be excluded from the structural equation. In a 2SLS model, the test statistic is constructed by regressing the estimated errors from the structural model of interest on all exogenous variables in the system. The number of observations times the uncentered R^2 from this synthetic regression is distributed as χ^2, with degrees of freedom equal to the number of instruments minus the endogenous right-hand-side variables in the structural equation of interest. In lines 3 and 4 of Table 6, we have two instruments and only one endogenous right-hand-side variable; therefore, the chi-squared test statistic has only one degree of freedom. Here again, we recognize that this is not a proper formal test; although the Angrist (1991) result allows us to accurately estimate the average treatment effect via two-stage least squares, it is not clear that the assumptions necessary to perform the tests of overidentifying restrictions are met when both *Y* and *QMB* are discrete. This class of tests is, however, the best available diagnostic.

In the final two columns of Table 6, we report the 2SLS estimate and, when appropriate, the test of overidentifying restrictions. Consistent with the results in Angrist (1991), the 2SLS estimates are similar in magnitude and precision to the average treatment effect estimated with the bivariate probit model. In all cases, the test of overidentifying restrictions is well below the 95 percent critical value and therefore, we cannot reject the null hypothesis that our instrument can be excluded from the probability of use equation.

In Table 7, we present estimates of the sample selection model outlined in equation (7). We report only estimates for log of Part B expenditures, because the QMB enrollment variable was not statistically significant in the single-equation estimates for Part A. For this table, we used the same instrument sets employed in Table 6. In column (1), we reproduce the single equation estimates from Table 3. For each model, we report the system estimate on the QMB enrollment variable and the coefficient on the sample selection correction term $\hat{H}$. Much like the results from the bivariate probit model, the two-step sample selection correction estimates are similar to the single-equation estimates, but the estimate on the QMB enrollment variable is imprecisely estimated.

The results from Tables 6 and 7 provide some evidence that for Part B expenditures, the single-equation estimates reported in Table 3 are not subject to bias due to adverse

Table 7
Two-Step Estimates of Intensity of Use Equation
Part B Expenditures

Parameter Estimates and Standard Errors

Variable	Model (1)	Model (2)	Model (3)	Model (4)
QMB enrollment	0.431 (0.106)	0.036 (0.553)	0.501 (0.357)	0.721 (0.567)
$\hat{H}$		0.241 (0.333)	-0.043 (0.217)	-0.170 (0.343)
Instrument Set		% Medicaid population that is elderly	% Medicaid population that is elderly, and it's square	% Medicaid population that is elderly, and # of QMB outreach programs (0-7)

Other exogenous variables include those listed in Table 3. Standard errors are calculated by the procedure suggested by Greene (1981). The results for model (1) are the single-equation estimates reported in table 3.

selection. However, the results are not precisely estimated. For Part A expenditures, we find no evidence that QMB enrollment increases the intensity of use, and in the bivariate probit results, we find little evidence that QMB alters the probability of Part A use. In general however, both the results for Part A and B expenditures are plagued by large variances on the parameters of interest.

CHAPTER 5

SUMMARY OF RESULTS

Since 1990, the Qualified Medicare Beneficiary program has required state Medicaid programs to pay the Medicare cost-sharing provisions for low-income Medicare beneficiaries. Payment of Medicare deductibles and copayments can be a serious economic hardship for QMB-eligible seniors; without the QMB program, many seniors may find it too costly to obtain some health services and subsequently may not seek medical care when needed.

This study's purpose was to determine whether there are systematic differences in Part A and B Medicare use between Medicare beneficiaries enrolled in the QMB program and those who are eligible for but not enrolled in the program. Using a standard two-part model of demand, we have estimated the impact of QMB enrollment on demand, controlling for factors as age, race, gender, education, income, marital status, health status, and region of country.

Our major findings are as follow:

- Among QMB-eligible seniors, the probability and intensity of Part B Medicare use are significantly higher among those enrolled in QMB than among those not enrolled.

- The probability of having any Medicare Part B utilization is 12 percentage points higher among individuals enrolled in QMB than among eligible non-enrollees. Among elderly Medicare beneficiaries that have any Part B use, Part B expenditures are 44% higher for those enrolled in QMB than for individuals who are not enrolled.

- The probability of having any Medicare Part A expenses is eight percentage points higher among QMBs than among eligible non-enrollees. However, there is no difference between these two groups in Part A expenditures for those who have any Part A charges.

- On average, QMB enrollees spend $1,900 more per year on health services covered by Medicare Part B and $1,300 more per year on Medicare Part A services than do eligible non-enrollees. Only 20 percent of the increase in Part B expenditures and about 100 percent of the increase in Part A use is attributable to a higher probability of use.

There is serious doubt as to whether these results can be interpreted as a causal effect of the QMB program. The health status of QMBs is poorer than those of eligible non-enrollees, and one would expect less healthy beneficiaries to have higher medical expenses regardless of QMB enrollment. Using standard econometric techniques for multi-equation systems, we have attempted to determine whether the observed relationship is causal.

Unfortunately, our results are not definitive. Some results suggest that the correlation between enrollment and use is solely a function of adverse selection, while other findings suggest that adverse selection does not explain the correlation. Additional research is needed to determine whether differences in expenditures among QMBs and eligible non-enrollees can be attributed to induced demand resulting from QMB enrollment or to adverse selection into the program.

CHAPTER 6

IMPLICATIONS

This study is the first to compare the health service utilization of low-income elderly Medicare beneficiaries enrolled in the Qualified Medicare Beneficiary program with that of elderly beneficiaries who are eligible for but not enrolled in the QMB program. We found that QMB enrollees, on average, use more medical services than do eligible non-enrollees. In addition, our findings indicate that the higher utilization levels of QMBs are associated with significant increases in Medicare program expenditures.

Table 8 describes the additional Medicare program costs that result as QMB enrollment increases at 5% intervals. For every 5% increase in proportion of the eligible population enrolled in the QMB program, there is a \$300 million increase in Part A expenditures and a \$443 million increase in Part B expenditures. As a result, the projected financial impact of the currently enrolled QMB population (representing 45% of those eligible for the program) is \$6.7 billion per year in 1993 dollars. Using a straight-line projection, we estimate that the financial impact of the program would reach \$14.9 billion if 100% of the eligible population were enrolled. This represents an upper-bound estimate, however, because those in the poorest health have already enrolled in the program (Neumann et al., 1994).

Previous reports on the QMB program have recommended research to compare out-of-pocket medical expenditures of QMBs and of eligible non-enrollees. These studies suggest

Table 8
Financial Impact of QMB Enrollment

Percent of the QMB eligible population enrolled in the program	Part A Financial Impact ($ billions)	Part B Financial Impact ($ billions)	Total Financial Impact ($ billions)
5	0.30	0.44	0.74
10	0.60	0.89	1.49
15	0.90	1.33	2.23
20	1.20	1.77	2.97
25	1.50	2.22	3.72
30	1.80	2.66	4.46
35	2.10	3.10	5.20
45	2.70	3.99	6.69
50	3.00	4.43	7.43
55	3.30	4.87	8.17
60	3.60	5.32	8.92
65	3.90	5.76	9.66
70	4.20	6.20	10.40
75	4.50	6.65	11.15
80	4.80	7.09	11.89
85	5.10	7.53	12.63
90	5.40	7.97	13.37
95	5.70	8.42	14.12
100	6.00	8.86	14.86

that the ratio of out-of-pocket expenditures to total income of these two populations would provide an indicator of access to care as among QMBs and eligible non-enrollees and would estimate the true financial impact of the QMB program. However, in light of the tremendous financial impact of the QMB program in its present form, it is clear that such analysis would not be fruitful; the additional expenditures representing beneficiaries' out-of-pocket costs for health services would pale in comparison to the amounts paid by the Medicare and Medicaid programs to cover QMBs.

CHAPTER 7

CONCLUSION

This study compares the health care use and expenditures of elderly Medicare beneficiaries enrolled in the Qualified Medicare Beneficiary program with those of eligible beneficiaries not enrolled in the QMB program. We estimated a two-part demand model to estimate the impact of QMB program participation on health care use and expenditures. By specifying the empirical model in this way, we avoided the problem of including an endogenous variable, namely QMB participation, as a regression variable to explain health service use. The study builds on previous analyses of characteristics of the QMB population. At the outset of this study, we outlined three research questions. Based on empirical results, we answer each of these questions below.

1) ***Among those eligible for the QMB program, are there significant differences in health care use among those enrolled and not enrolled? If so, are these differences specific to Part A or Part B reimbursed services?***

   We found significant differences in health care use and expenditures between Medicare beneficiaries enrolled in the QMB program and eligible beneficiaries who are not enrolled. Using the National Claims History File, we separated these differences into Part A and Part B reimbursements. The expenditure difference between the two groups was larger for Part B services than for Part A services.

2) ***Is there any evidence of adverse selection among Medicare beneficiaries who have enrolled in the QMB program?***

We found strong evidence of adverse selection among beneficiaries enrolled in the QMB program. We found that overall, the health status of beneficiaries enrolled in the program was worse than that of eligible non-enrollees. Our claims data analysis revealed that poorer health status was associated with increased health care use and expenditures. As discussed briefly in Chapter Five, we need to develop better identifying restrictions to truly test for the presence and extent of adverse selection in the econometric models.

3) What is the impact of QMB enrollment on Medicare expenditures?

In Table 8 we provide an approximate estimate of the impact of QMB enrollment on Medicare program expenditures. In 1993 dollars, the current additional burden of the QMB program is $6.7 billion. This amount does not include the base level of health care resources that would be spent if individuals did not qualify for the QMB program. We tend to view the financial impacts reported in Table 8 as an upper bound, because the proportion of QMB-eligibles in poorest health have already enrolled in the program. Consequently, increases in QMB program participation may be associated with decreasing per-capita expenditures in the future.

In summary, our analysis demonstrates that the QMB program has achieved its goal of increasing access to medical services for elderly low-income Medicare beneficiaries. It is clear that QMB-eligible beneficiaries who are enrolled in the program are utilizing its benefits. Our findings suggest several areas for future research. To provide a more precise estimate of the true costs of the QMB program, it would be useful to conduct a longitudinal analysis of the costs of treating a cohort of QMB-eligible beneficiaries over time. Access to Part B services through the QMB program may prevent catastrophic health events that would have been expensive to treat, or it may only forestall them temporarily. In addition, access to Part B services could eliminate or diminish ongoing health problems that beneficiaries previously lacked the resources to treat. If these situations are prevalent, the financial impact we have reported overestimates the true cost of the QMB program. Only a cohort study could provide a definitive answer as to whether the QMB program reduces health expenditures over time.

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